Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Unveiling the Human-Climate Nexus through the CLIMAgenAI framework: a Multi-Source Causal Framework for Climate Risk Analysis and AI-Supported Disaster Governance

Edda Donati
University of Rome Tor Vergata
Andrea Paolini
University of Rome Tor Vergata
Floriana Rizzo
University of Rome Tor Vergata
Luciano Pavesi
University of Rome Tor Vergata
Fernando Nardi
fernando.nardi@uniroma2.eu

University of Rome Tor Vergata

Article

Keywords: CLIMAgenAI, Multi-source causal framework, Cause–effect matrix, Generative artificial intelligence, Climate Knowledge, Forensic climate risk governance

Posted Date: August 25th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-10664382/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: No competing interests reported.

Unveiling the Human-Climate Nexus through the CLIMAgenAI framework: a Multi-Source Causal Framework for Climate Risk Analysis and AI-Supported Disaster Governance

Edda Donati[1,2] Andrea Paolini[1], Floriana Rizzo[1], Luciano Pavesi[1] and Fernando Nardi[1,*]

[1] Department of Civil Engineering and Computer Science, University of Rome Tor Vergata, Rome, Italy

[2] Fondazione Eni Enrico Mattei (FEEM), Milan, Italy

*Corresponding author: fernando.nardi@uniroma2.eu

Abstract

Climate risk emerges from the interaction of hazards, exposure and vulnerability within complex socio-economic and governance systems, yet existing approaches to risk assessment often remain fragmented across disciplines and rely on sector-specific assessment and mitigation methods that rarely capture complex multi-sector event trajectories. This paper introduces CLIMAgenAI, a multi-source causal framework that extends the classical cause–effect matrix to integrate judicial rulings, archival records and multimedia materials into a unified process-based representation of climate-related disasters. Building on Fault Tree Analysis (FTA), Event Tree Analysis (ETA) and Human and Organizational Factors Engineering (HOFE), CLIMAgenAI systematically extracts and codes causal relations from narrative and visual documents, reconstructing multi-level pathways linking natural, contextual and institutional factors to disaster outcomes. The framework is demonstrated through the 1998 Sarno (Italy) debris-flow disaster and produces structured outputs—including extended cause–effect matrices, causal pathways and comparative datasets—that provide a knowledge base for AI-supported climate risk communication, stakeholder engagement and forensic disaster governance. Unlike previous approaches that analyse individual sources separately, CLIMAgenAI reconstructs climate-related disasters through a unified causal representation integrating judicial, archival and multimedia evidence. The objective is not to develop a new GenAI approach itself, but to demonstrate that integrating heterogeneous documentary sources into a standardized causal framework creates a robust, replicable and scalable knowledge base for future AI-supported analysis and decision support.
.

Keywords: CLIMAgenAI, Multi-source causal framework, Cause–effect matrix, Generative artificial intelligence, Climate Knowledge, Forensic climate risk governance

1. Introduction

Climate risk arises from the interaction of hazards, exposure and vulnerability within complex socio-economic and governance systems, affecting physical infrastructures, ecosystems, economies and societies (Hochrainer-Stigler et al. 2024; Fajardo-Gonzalez et al. 2025; Huang et al. 2022; Attoh and Amarnath 2025).

Despite extensive research on climate risk, two major knowledge and governance gaps remain: the fragmented sector-specific way in which climate risk is analyzed and mitigated. The second limitation

concerns the limited observation, monitoring and documentary evidence used to reconstruct climate-related disasters.

The first issue, namely fragmentation across disciplines, is largely a consequence of the systemic complexity that characterizes climate risk. Engineering, social sciences, economics and legal studies tend to analyze it through sector-specific approaches, treating it as an isolated phenomenon rather than as a component of a multi-level socio-ecological system (Moser and Ekstrom 2010; Gallina et al. 2016; Aven 2016; O'Brien et al. 2007; Osborne and Fleming 2015). This fragmentation limits the ability to fully understand the different dimensions of risk and the role of institutional arrangements in shaping vulnerability and the severity of impacts (Moser and Ekstrom 2010).

Building on these insights, numerous studies have shown that disaster impacts depend not only on the biophysical characteristics of hazards, but also on pre-existing contextual vulnerabilities and on interrelated institutional and behavioral failures that individual risk and prevention disciplines struggle to capture in an integrated way. Contextual vulnerability includes territorial, infrastructural and governance conditions — such as urban planning, institutional coordination and emergency preparedness — that influence how hazards translate into damage (Birkmann 2013; Bacon 2010; Gallina et al. 2016). At the same time, behavioral and organizational dimensions, including risk perception, decision-making processes, communication practices and the activation of emergency measures, play a crucial role in amplifying or mitigating disaster outcomes (Rasmussen 1997; Boin et al. 2005; K. J. Tierney 2014).

The second issue concerns the technologies, empirical tools and documents used in climate risk observation, monitoring and analysis across different sectors. In this work we focus on post-disaster reporting for understanding causes and assessing impacts. In practice, risk assessment relies largely on technical reports, regulatory plans and sector-specific indicators, which provide detailed monitoring data and readings of risk within individual domains but rarely allow the event to be reconstructed in its entirety. Numerous reviews have shown that such approaches, often mono-hazard and mono-sector, struggle to integrate interdependencies between systems and socio-institutional dimensions, with a consequent loss of information on the causal chains linking decisions, failures and impacts (Gallina et al. 2016; Aven 2025, 2016). At the same time, tools based on composite indices and indicators tend to synthesize exposure and vulnerability without making the underlying causal mechanisms explicit, while the disaster risk governance literature highlights the need to represent decision-making and organizational processes that produce vulnerability and amplify disaster outcomes in an explicit way (Moser and Ekstrom 2010; Rasmussen 1997; K. J. Tierney 2014).
This research aims to address these gaps by developing an innovative methodological framework, CLIMAgenAI, which adapts the classic cause–effect matrix — originally used in engineering and risk assessment — to the analysis of different types of information sources. The framework responds to the previously identified gaps along both dimensions. On the one hand, the adoption and further development of the cause–effect matrix within the framework provide an in-depth and unified reconstruction of the event and of the multi-level causal pathways that determine its outcomes. On the other hand, the methodology, grounded in the principles of Fault Tree Analysis (FTA), Event Tree Analysis (ETA) and Human and Organizational Factors Engineering (HOFE), can be adapted and applied to the analysis of different technical reporting and documentary sources (technical reports, judicial decisions, multimedia materials and archival records), offering a replicable multi-sector multi-source tool to analyze multi-level institutional performance in disaster contexts.
The manuscript is structured as follows. Section 2 presents the conceptual and methodological foundations of the CLIMAgenAI framework, with a specific focus on the cause–effect matrix and the integration of FTA, ETA and HOFE. Section 3 illustrates CLIMAgenAI methodological and case study application valuing available judicial decisions, multimedia materials and archival records of the historical1998 Sarno flood, Italy. Section 4 discusses how the structured outputs of CLIMAgenAI

can be integrated into AI-supported tools for improved disaster governance, climate risk communication and stakeholder engagement. Section 5 presents the main conclusions and outlines limitations and future developments of this work.

2. Conceptual foundations: reverse-engineering risk through cause–effect matrix

The CLIMAgenAI framework builds on the use of the cause–effect matrix, traditionally used in engineering and climate risk assessment, as a multi-sector transdisciplinary tool to integrate hazard, vulnerability and exposure data from diverse sources and transfer risk information fostering multi-sector risk governance and decision making. This methodological choice responds to the need for a systematic and replicable procedure capable of extracting, classifying and comparing information from heterogeneous documentary and visual sources, and of reconstructing a single chain of causes and effects characteristic of each event, providing a comprehensive and exhaustive description of its dynamics. The framework is grounded in the classical risk formulation widely adopted in multi-risk and climate risk assessment:

$$R = P \times D = P \times E \times V \quad (1)$$

Risk is conceived as a function of the probability P that a hazardous event will occur and the magnitude of the resulting damage D, which in turn is determined by the combination of exposure E and vulnerability V associated with that event (Duijm 2015; Ekström et al. 2013; Basu 2017; Akçay Zileli 2023; Moseman 2024).

In the CLIMAgenAI framework, exposure and vulnerability are not introduced as predefined external variables but are instead derived empirically from the analysis of documentary sources through the cause–effect matrix. In other words, E and V are used to derive and evaluate the synergetic effect of physical components, socio-economic systems and behavioral human-related elements whose interplay governs the risk dimension. It should be noted that the P hazard component is, at present, considered as intrinsically defined and associated to the biophysical dimensions that are either observed, monitored or assessed using engineering analyses. Nonetheless, the P component is also processed together with E and V by means of the CLIMAgenAI analytical method.

The CLIMAgenAI framework — grounded in the cause–effect matrix described above — enables the systematic extraction of causal relations present in judicial, archival and multimedia sources that contribute to determining levels of exposure and vulnerability. As in traditional models, these elements, together with hazard data, constitute the basis for risk assessment. In this way, the analytical framework links classical risk formulation $R = P \times E \times V$ to the reconstruction of causal pathways emerging from the documentary sources analysed (Figure 1).

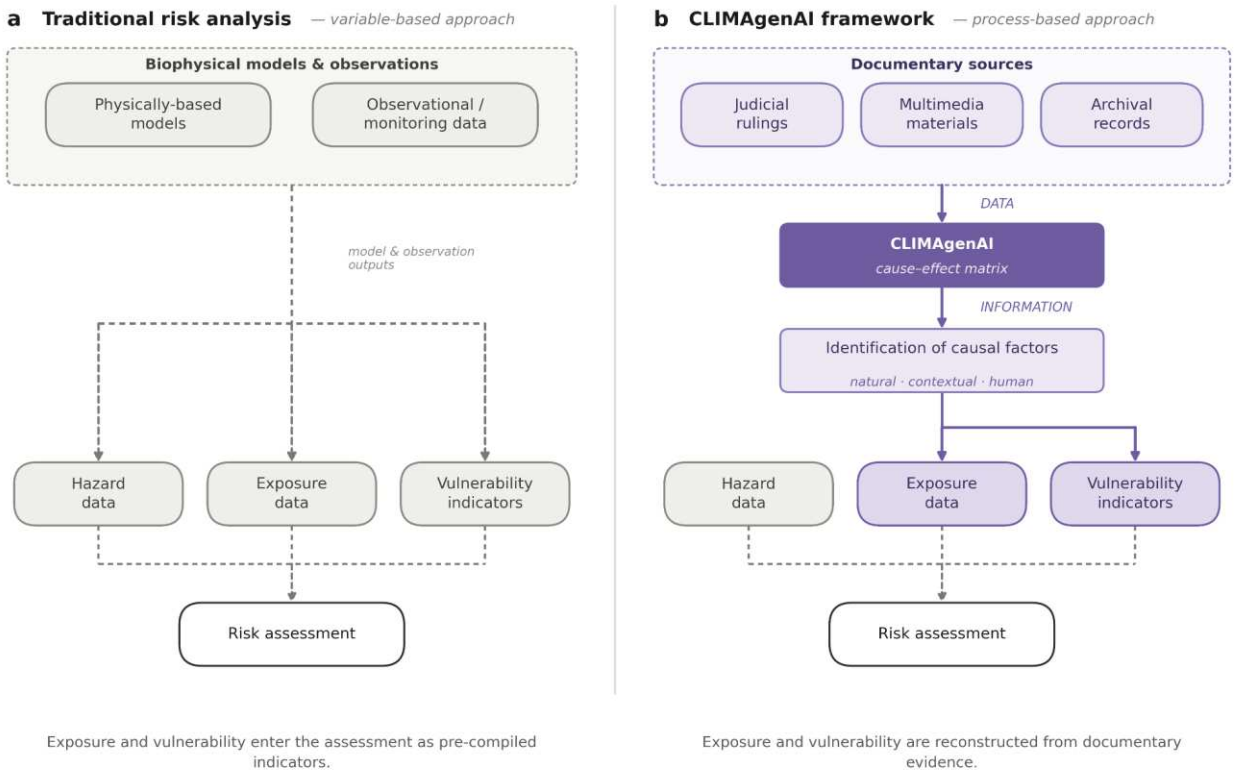


Figure 1. Comparison between the traditional risk analysis model and the proposed CLIMAgenAI framework

The use of documentary sources (i.e. produced by humans in the form of both engineering reporting, social, economic or judicial analyses) enables a more human-centered interpretation of risk, in which vulnerability is understood not only as a physical or structural condition, but as the outcome of governance arrangements, institutional performance and human decision-making processes.

The widespread use of the cause–effect matrix in climate and environmental risk management derives from its capacity to decompose complex risk processes into analytically identifiable components, to facilitate comparison across heterogeneous events, and to organize qualitative and quantitative information into structured categories (Duijm 2015; Gallina et al. 2016). To reinforce and extend this capacity within the CLIMAgenAI framework, the analysis integrates concepts drawn from three complementary approaches: Fault Tree Analysis (FTA), Event Tree Analysis (ETA) and Human and Organizational Factors Engineering (HOFE). Each method contributes to identifying specific dimensions of the causal process and provides the analytical foundations for the functioning of the matrix.

FTA is a deductive, top-down method used to analyze the potential causes of an undesired event or system failure. It constructs a logical diagram using AND, OR connectors to represent relationships between a top-level failure event and the underlying events — related to technical components or human errors — that may produce it (Wessiani and Yoshio 2018; Ehiagwina 2022; Yazdi et al. 2023; Khan and Husain 2001). Within CLIMAgenAI, the contribution of FTA lies in the systematic decomposition of failure events into their primary causes, enabling the identification of critical causal pathways and the understanding of how combinations of factors can propagate within complex systems (Yazdi et al. 2023; Ehiagwina 2022; Brignone et al. 2025).

ETA is a risk assessment method oriented towards the reconstruction of evolutionary scenarios. Starting from an initiating event, it systematically maps possible developments and evaluates the role

of preventive and mitigative barriers — effective or failed — that influence the probability and severity of consequences (Baraldi and Zio 2008; Pasman and Rogers 2020; Rosqvist et al. 2013; Ferdous et al. 2013; Čepin 2011). In the context of the cause–effect matrix, ETA supports the reconstruction of event trajectories and the understanding of conditions that transform a hazard into damage.

The third approach integrated into the framework is HOFE, a discipline that incorporates insights from human and social sciences — such as cognitive psychology, sociology and organizational behavior — into the analysis of technical systems, in order to better understand how human and organizational factors influence the emergence and propagation of failures in socio-technical systems (Rasmussen 1997; Ferdous et al. 2009; Skogdalen and Vinnem 2011; Trist and Bamforth 1951). The integration of the HOFE perspective allows the cause–effect matrix to incorporate dimensions often neglected in traditional technical models, such as decision-making processes, organizational dynamics, communication practices and safety culture.

By combining the causal structure of FTA, the scenario-oriented analysis of ETA and the behavioral and organizational dimensions introduced by HOFE, the CLIMAgenAI framework integrates different domains of application into a single analytical scheme, including social sciences, governance analysis and the study of cultural heritage and historical-documentary and visual sources.

3. Materials and method

3.1 CLIMAgenAI framework and application

3.1.1 Judicial rulings

Judicial rulings remain a relatively under-used yet highly informative source for analyzing climate disasters. They provide detailed reconstructions of events, identify omissions and administrative failures, and articulate causal chains linking institutional behavior to disaster outcomes (K. J. Tierney 2014b; Boin et al. 2005; Rasmussen 1997). Court decisions can be regarded as comprehensive archives of quantitative and qualitative information on disaster events, as well as historical records of climate impacts. Through legally structured narratives, rulings explicitly assess institutional duties, omissions and causal relationships that in other disaster information sources (e.g. earth observation, civil protection reports) often remain implicit or fragmented (Ferdous et al. 2013; Skogdalen and Vinnem 2011; K. Tierney 2012).

From a climate risk perspective, the relevance of judicial material is therefore twofold. On the one hand, rulings contain numerical data — such as the number of fatalities and seriously injured persons — together with qualitative assessments regarding performances or failures of early warning systems, levels of preparedness and the effectiveness of emergency response measures. By integrating these elements within a legally grounded causal narrative, judicial decisions create a bridge between quantitative indicators and qualitative interpretations, allowing cause–effect relations that are only partial or implicit in other data sources to be reconstructed more explicitly.

On the other hand, judicial decisions pose significant methodological challenges. Their structure varies across courts and instances; legal reasoning follows doctrines and procedural rules that do not necessarily align with scientific categories; and information is often dispersed across long, complex texts (Gallina et al. 2016; Pahl-Wostl 2009). As a result, disaster and climate risk research rarely uses court rulings as a primary, systematic data source and even less frequently attempts to translate judicial reasoning into formal causal frameworks consistent with quantitative risk science and data metrics.

Within the CLIMAgenAI framework, judicial rulings are, therefore, approached as process-based documentary sources that can be systematically transformed into structured causal information, extending and standardizing the approach developed by Donati and Nardi (2026). Court decisions are treated as invaluable sources of information for understanding climate-related events and the ways in which multiple sectors influence both the occurrence of the event and its consequences. However, unlike the previous work, the present study introduces a standardized framework that can be applied to rulings concerning heterogeneous disaster categories and integrates them with other documentary sources, whereas Donati and Nardi (2026) focused exclusively on flood disasters and on judicial material alone.

The analytical procedure, illustrated in Figure 2, consists of three main methodological steps: input, analytical actions and output. In the input stage, relevant rulings are selected across different judicial instances, and their event-related physical information is compiled, including date and location of the event, type of hazard and meteorological warnings, technical descriptions of impacts and judicial outcomes. In the analytical stage, legal texts are segmented and standardized, identifying key variables and converting legal statements into analytical units. A rule-based hierarchy of reliability is applied to handle inconsistencies across different degrees of judgment and to document uncertainties. Narratives are, then, subjected to causal coding, whereby explicit and implicit statements about decisions, omissions and institutional responsibilities are translated into cause–effect relations. These relations are categorized into natural, contextual and behavioral dimensions, in line with the integration of FTA, ETA and HOFE in the CLIMAgenAI framework (Duijm 2015; Rasmussen 1997; Skogdalen and Vinnem 2011; Čepin 2011). In the input stage, two main types of information are extracted from judicial rulings. First, the full texts of the decisions are collected, including different instances and the corresponding reconstructions of responsibilities. Second, event-related information described in the rulings is compiled, such as the date and location of the event, type of risk and weather warnings, technical descriptions of the event and its impacts, the number of victims and the judicial outcomes.

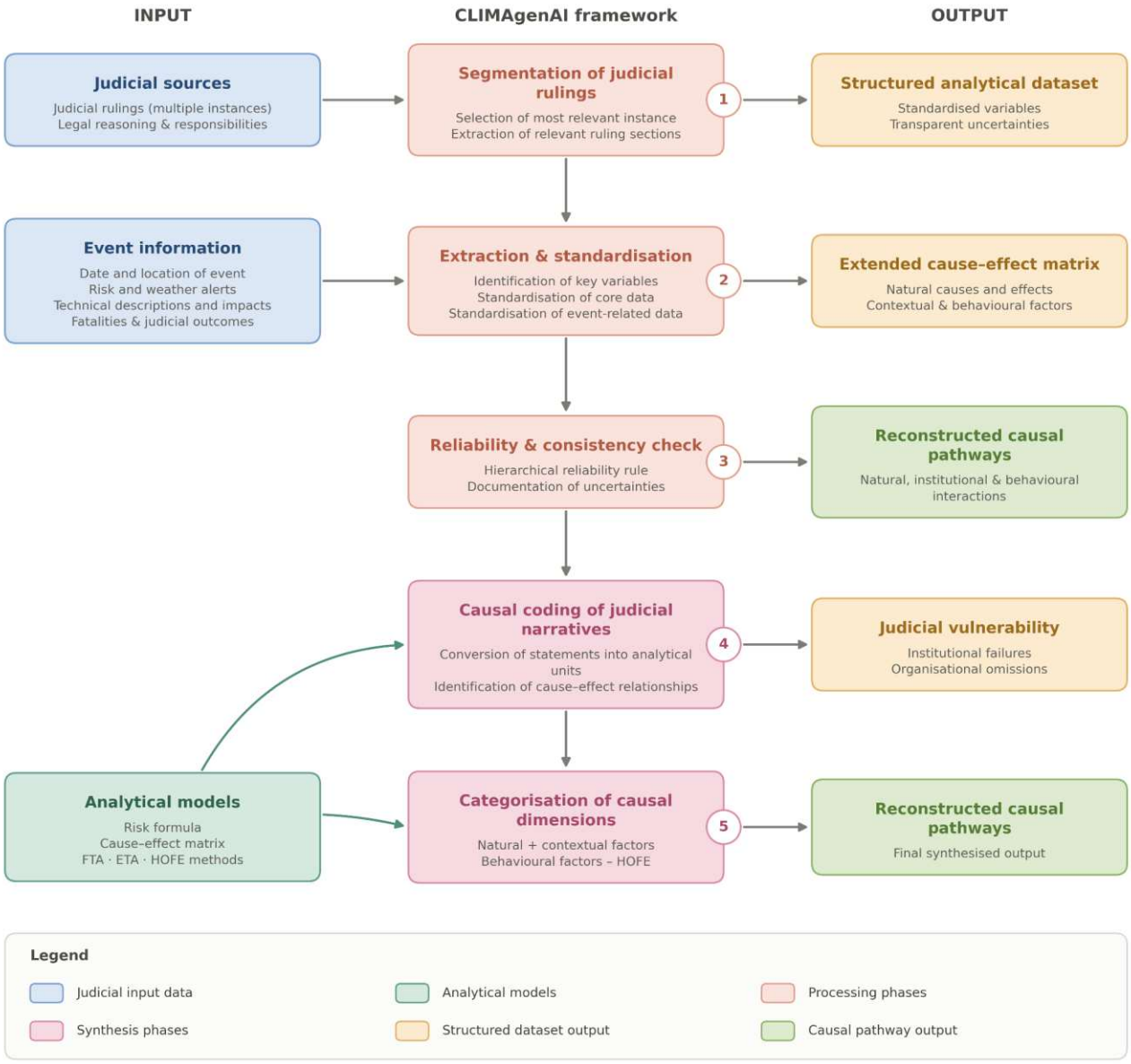


Figure 2. CLIMAgenAI framework for analyzing judicial sources through the cause–effect matrix

The analytical stage comprises a set of processing actions. Judicial decisions are initially segmented by selecting the most relevant instance and identifying those sections that contain essential information for reconstructing events. The extracted information is then standardized by identifying key variables and organizing them into a structured dataset. This process includes a verification step to assess the reliability and consistency of the information, based on a hierarchical reliability rule that gives priority to the dispositive sections and to higher-instance judgments, while explicitly recording uncertainties or discrepancies between sources. Once the data has been structured, judicial narratives undergo causal coding. This involves converting statements contained in the rulings into analytical units and identifying cause–effect relationships between events, institutional decisions and disaster consequences. The information is organized into three distinct causal dimensions — natural factors, contextual factors and behavioral factors — in line with the integrated use of FTA, ETA and HOFE (Donati and Nardi, 2026).

The output stage produces, first, a structured analytical dataset in which information from the rulings is standardized and made comparable across cases. On this basis, an extended cause–effect matrix is constructed, systematically representing relationships between natural causes, institutional factors and organizational behaviors. This matrix allows the reconstruction of causal pathways leading to disaster outcomes, highlighting the interaction between natural, institutional and behavioral components. The analysis ultimately identifies forms of institutional vulnerability, such as organizational failures, administrative omissions and weaknesses in governance systems.
Overall, this process allows the transformation of judicial rulings from narrative legal documents into comparable analytical structures, enabling the systematic examination of institutional responsibilities and of the mechanisms through which the hazard-to-risk process is governed and impact sourcing dynamics in climate-related disasters.

3.1.2 Multimedia sources

The cause–effect matrix, already successfully tested to value information derived from judicial sources (Donati and Nardi, 2026), can be used to analyze textual documentary material by reconstructing the causal structure of events through an analytical approach based on FTA, ETA, and Human and HOFE. However, unlike applications that rely exclusively on textual documentation, multimedia analysis involves images, photographs, historical maps, technical drawings and other visual materials that do not always come with descriptive text that can be directly processed through the CLIMAgenAI framework. Nonetheless, recent advances in vision–language models (VLMs) have demonstrated that visual information can be systematically transformed into semantic textual representations, enabling images to be integrated into analytical workflows traditionally designed for textual data (Bordes et al. 2024; Karpathy and Fei-Fei 2014; Radford et al. 2021).

For this reason, while the analytical structure of the cause–effect matrix remains unchanged, the analysis of multimedia sources requires a preliminary methodological phase aimed at transforming unstructured visual documentation into structured textual information (Figure 3). This process is conceptually consistent with image captioning and semantic image interpretation approaches developed in computer vision and multimodal artificial intelligence, where visual content is converted into machine-readable textual descriptions (Karpathy and Fei-Fei 2014; Radford et al. 2021).

The methodological process underlying information extraction draws on the logic of the cataloguing schemes used in the Italian National Cataloguing System for Cultural Heritage (ICCD – namely Istituto Centrale per il Catalogo e la Documentazione), which describe and contextualize iconographic sources through a structured set of metadata (Table 1). The aim of the process is not to provide a full art-historical cataloguing of the image, as required by ICCD, but rather to transform each multimedia source into structured textual descriptors that are useful for subsequent causal analysis, in combination with textual sources relating to the same event used to construct the cause–effect matrix (ICCD, 2005).

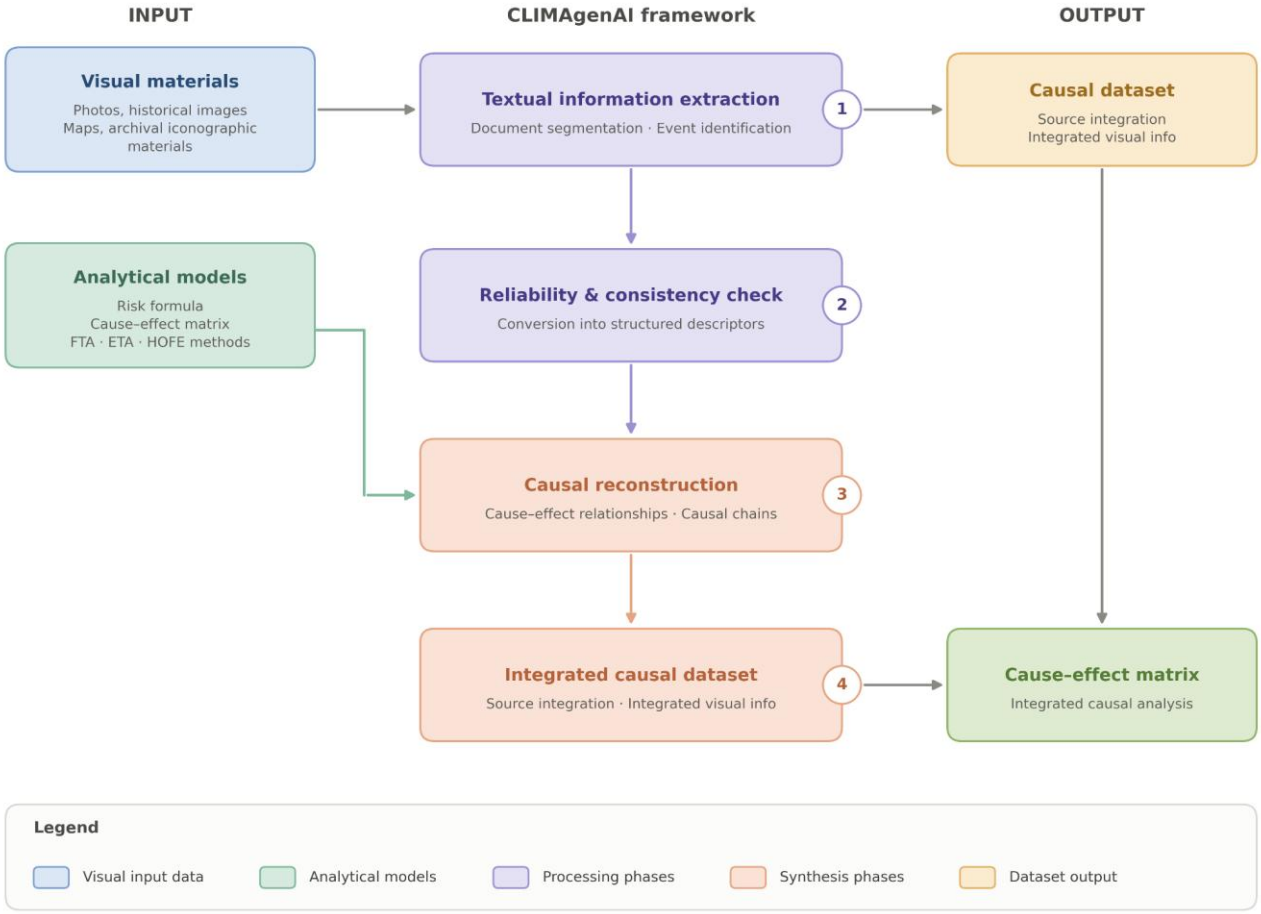


Figure 3. CLIMAgenAI framework for analyzing multimedia sources through the cause–effect matrix

Category	**Source Typology**	**Description**	**Adoption in the CLIMAgenAI Framework**
Identification	Source ID	Unique identifier assigned to the source	Ensures source traceability
Identification	Source type	Photograph, map, engraving, technical drawing, archival image	Classifies the documentary source type
Provenance	Archive / Collection	Archive or collection from which the source originates	Assesses source reliability and archival context
Provenance	Archival reference	Archival signature or catalog reference	Links the source to its archival collection
Contextualization	Dating	Date or historical period of the image	Places the documented event in its temporal context
Contextualization	Location depicted	Geographic location or place name represented	Links the source to spatial and territorial events

Visual description	Brief description	Objective summary of the visual content	Converts the visual source into structured textual information
Natural features	Visible natural factors	River, landslide, snow, water, debris, erosion, etc.	Identifies natural hazards and environmental processes
Anthropogenic features	Structures and infrastructure	Buildings, bridges, roads, levees, hydraulic works	Identifies exposure elements and the built environment
Impact evidence	Damage or transformation evidence	Flooding, collapses, debris accumulation, infrastructure damage	Documents of the observed impacts of the event
Documentary links	Associated textual document	Report, court ruling, newspaper article, or related document	Links the visual source to the textual corpus
Analytical output	Causal information units	Information converted into standardized analytical descriptors	Serves as input for the cause–effect analytical matrix

Table 1. Metadata scheme for multimedia sources in the CLIMAgenAI framework

Once all relevant information has been extracted from each multimedia source, these elements are converted into standardized textual descriptors (descriptive and contextual components) and integrated into the broader documentary corpus to be analyzed, together with other textual sources. From this integrated corpus, the cause–effect matrix is subsequently derived.

The integration of visual and textual sources makes it possible to build a unified documentary dataset in which information is organized within a common analytical structure. This multimodal integration enables heterogeneous documentary evidence to be represented through a unified semantic framework, consistent with recent developments in vision–language modeling and multimodal learning (Bordes et al. 2024).

3.1.3 Archival sources

Archival sources are a fundamental component of historical-documentary disaster analysis, as they include administrative records, technical reports, institutional communications, historical chronicles and other materials produced during the management and reconstruction of hazardous events. These documents often constitute one of the main sources of information available for reconstructing event dynamics and the decision-making processes that have influenced risk management over time.

Unlike multimedia sources, archival materials typically have an explicit textual structure, which allows for direct analysis of the information contained and facilitates the identification of elements relevant to event interpretation. At the same time, archival documentation is frequently characterized by high heterogeneity in terms of document format, language, level of detail and original purpose. This heterogeneity makes a preliminary process of segmentation, selection and normalization necessary to render data from different documents comparable.

The analytical procedure, therefore, begins by decomposing archival documents into elementary information units, corresponding to sentences or text passages that describe events, territorial conditions, infrastructures, institutional decisions or observed consequences. Attention is devoted to identifying information that can be used to reconstruct relationships between natural factors, contextual conditions and institutional or behavioral dynamics, as these elements are central to the

causal chains that characterize disaster events and form the basis for applying the proposed cause–effect matrix framework.

Once identified, these information units are coded into comparable analytical categories that allow data from different documentary sources to be integrated within a common informational structure. Through this coding process, heterogeneous narrative archival material is transformed into a structured documentary dataset, in which information is organized according to analytical categories consistent with the logic of the cause–effect matrix. This data set becomes a key input for reconstructing causal relationships among natural, contextual and institutional factors.

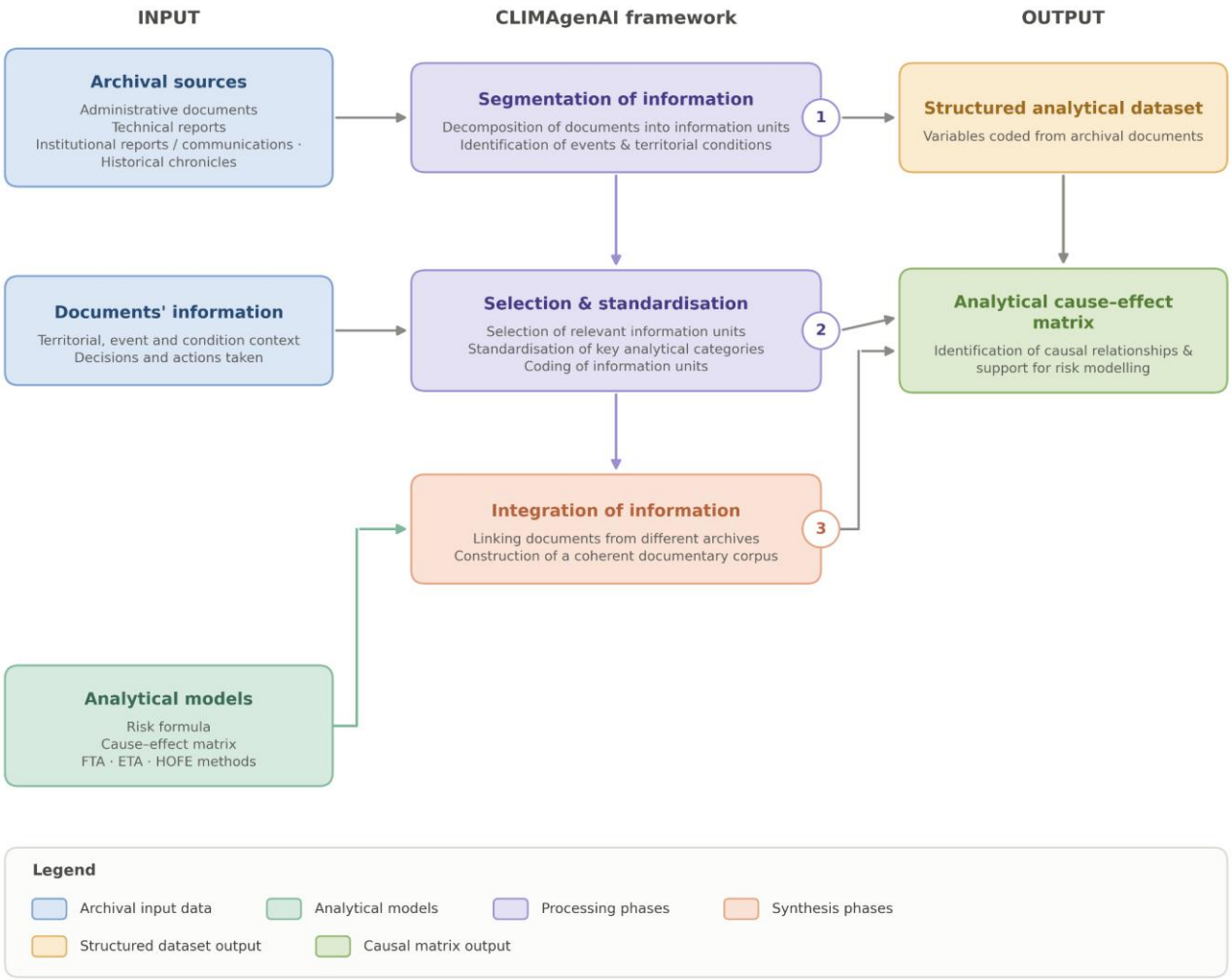


Figure 4. CLIMAgenAI framework for analyzing archival sources through the cause–effect matrix

Figure 4 summarizes the CLIMAgenAI framework for analyzing archival sources through the cause–effect matrix. Archival documents are first segmented and standardized, extracting core variables related to hazards, exposure conditions, vulnerabilities and institutional actions. These variables are then organized into a structured dataset and mapped into the cause–effect matrix, which represents how decisions, omissions and contextual factors combine and propagate towards specific outcomes. In this way, archival sources are transformed from dispersed narrative records into a coherent structured analytical basis for reconstructing causal pathways and identifying forms of institutional vulnerability, such as organizational failures, administrative omissions and governance weaknesses.

3.1.4 Case study adaptation and variables

The CLIMAgenAI framework was applied to the 1998 Sarno flood, a debris-flow disaster in which hillslope rainfall-driven mudslides rapidly generated and propagated from steep slopes to the downstream village causing fatalities, disruption and extensive destruction in the affected area. This case study was selected because it provides an illustrative example for demonstrating how the CLIMAgenAI framework operates. It is characterized by a rich heterogeneous documentary record across archival, multimedia and judicial domains, which allows for a comprehensive reconstruction of the event and a systematic comparison of what each source contributes. The analysis shows, for each source type, the information that is available and how its integration within the framework yields a more complete and exhaustive understanding of the event.

Table 2 summarizes the main characteristics of the Sarno event and lists all the sources analyzed for the case study in the three data source categories considered: judicial, multimedia and archival.

Place	**Type**	**Year**	**Judicial source**	**Multimedia source**	**Archival source**
Sarno (SA), Campania	Flood	1998	cass-civ-sez-iii-ord-data-ud-10-02-2025-16-04-2025.pdf	M1:ANSA; news agency; 1998; M2: "The Sarno flood, twenty years on"; il Post; 2018; M3: Sky TG24; M4: ESRI; M5: POLARIS (IRPI-CNR); research institute; 2018;	A1: "Fango – Il modello Sarno vent'anni dopo"; Legambiente; 2018; A2: "Sarno 1998 – Il disastro di fango"; Italian Civil Protection Department;

Table 2: Documentary sources used in the CLIMAgenAI case studies (judicial, multimedia (M) and archival (A) sources

A set of variables was then identified to support the case study systematic description and structured interpretation. These variables were coded across all available sources (judicial, multimedia and archival) and captured both the characteristics of the event itself and the physical, social, economic and psychological dimensions that contributed to its occurrence and severity. The variables were subsequently grouped into broader categories, and the information extracted was used to populate the cause–effect matrix describing the event, which constitutes the main output of the CLIMAgenAI framework. Table 3 presents the variables included in the dataset, the possible values adopted for the analysis of future case studies beyond the Sarno event already examined in this paper, together with a short description of each variable.

Category	**Variable**	**Possible values**	**Description**
Observations	Natural_Element	List	List of natural features observed in the case (e.g. river, slope, forest, snow, debris).
	Hazard_Evidence	List	Direct visual or documentary evidence of hazardous processes (e.g. flood marks, landslide scars).
	Meteorological_Conditions	List	Weather conditions associated with the event (e.g. intense rainfall, snow, storm).

	Anthropogenic_Element	List	Human-made structures and infrastructures present in the area (e.g. buildings, bridges, roads, levees).
	Exposure_Element	List	Elements exposed to the hazard (e.g. population, residential areas, industrial sites, transport networks).
	Vulnerability_Evidence	List	Observable signs of physical or social vulnerability (e.g. poor maintenance, informal housing, isolation).
	Human_Action_Observed	List	Observed human actions during the event (e.g. evacuation, self-protection, risky behaviour).
	Organizational_Action_Observed	List	Observed organisational actions (e.g. activation of emergency plans, coordination meetings).
	Prevention_Measure_Observed	List	Pre-existing preventive measures visible in the case (e.g. levees, monitoring devices, land-use rules).
	Emergency_Action_Observed	List	Emergency actions implemented during or immediately after the event (e.g. warnings, rescue operations).
	Impact_Observed	List	Directly observed impacts (e.g. flooding, building collapse, road interruption).
	Consequence_Observed	List	Longer-term or systemic consequences (e.g. displacement, economic disruption, environmental degradation).
Hazard classification	Hazard_Type	Flood / Flash Flood / Landslide / Debris Flow / Storm / Snow / Drought / Other	Type of hazardous process primarily responsible for the event.
	Exposure	Population / Buildings / Infrastructure / Economic Activities / Cultural Heritage / Environment	Main categories of elements exposed to the hazard.
	Physical_Vulnerability	None / Low / Medium / High	Level of physical fragility of exposed elements.

	Environmental_Vulnerability	None / Low / Medium / High	Sensitivity of environmental components to the hazard.
	Social_Vulnerability	None / Low / Medium / High	Level of social vulnerability (e.g. age, income, isolation).
	Economic_Vulnerability	None / Low / Medium / High	Susceptibility of economic activities and assets to damage.
Human factors	Human_Factor	Yes / No	Whether human factors are explicitly present in the causal chain.
	Human_Action	Short text	Short description of key human actions influencing the event.
	Human_Error	Yes / No	Whether the case documents explicit human errors.
	Unsafe_Behaviour	Yes / No	Presence of unsafe behaviours increasing risk.
	Risk_Underestimation	Yes / No	Evidence that risk was underestimated by individuals or groups.
	Evacuation_Delay	Yes / No	Presence of delays in evacuation decisions or actions.
Organizational factors	Organizational_Factor	Yes / No	Whether organisational factors are explicitly present in the causal chain.
	Governance_Issue	Yes / No	Presence of governance problems (e.g. unclear responsibilities, legal gaps).
	Coordination_Problem	Yes / No	Problems of coordination among institutions or agencies.
	Communication_Problem	Yes / No	Problems in communication of warnings or information.
	Planning_Issue	Yes / No	Issues related to land-use, emergency or infrastructure planning.
Decision-making	Decision_Made	List	Description of key decisions taken before or during the event.
	Decision_Error	Yes / No	Presence of wrong or misguided decisions.
	Decision_Delay	Yes / No	Presence of delays in decision-making.

	Inappropriate_Decision	Yes / No	Presence of decisions judged inappropriate in the legal or documentary record.
Prevention measures	Prevention	Present / Absent / Not inferable	Overall presence of preventive measures in the case.
	Structural_Protection	Present / Absent	Presence of structural protection works (e.g. levees, barriers).
	Monitoring_System	Present / Absent	Presence of monitoring or early warning systems.
	Maintenance	Adequate / Inadequate / Unknown	Quality of maintenance of protective structures and systems.
	Land_Use_Planning	Present / Absent	Presence of land-use planning instruments relevant to the hazard.
Emergency management	Early_Warning	Present / Absent	Presence of early warning messages before the event.
	Emergency_Response	Adequate / Delayed / Absent	Quality and timeliness of emergency response actions.
	Rescue	Present / Absent	Presence of search and rescue operations.
	Evacuation	Present / Absent	Presence of organized evacuation.
	Crisis_Coordination	Adequate / Inadequate	Quality of crisis coordination across actors and levels.
Impacts	Flooding	None / Localized / Extensive	Extent of flooding in the case.
	Building_Damage	None / Minor / Major / Destroyed	Level of damage to buildings.
	Infrastructure_Damage	None / Minor / Major / Destroyed	Level of damage to infrastructures.
	Environmental_Damage	None / Minor / Major	Level of damage to environmental components.
	Economic_Damage	None / Minor / Major	Magnitude of economic losses.
	Human_Losses	None / Injuries / Fatalities	Human impacts in terms of injuries and deaths.

Table 3. Variables included in the CLIMAgenAI dataset, their possible values and a short description

Figure 5 shows how these variables are mapped onto the different fields of the cause–effect matrix. The matrix is organized into two main macro-groups (Causes and Effects), each subdivided into three sub-groups: natural, contextual and behavioral. The natural dimension encompasses variables related to hazards and physical processes; the contextual dimension captures territorial, infrastructural and

socio-economic conditions; and the behavioral dimension includes human and organizational actions, decisions and failures that influence the evolution and impacts of the event.

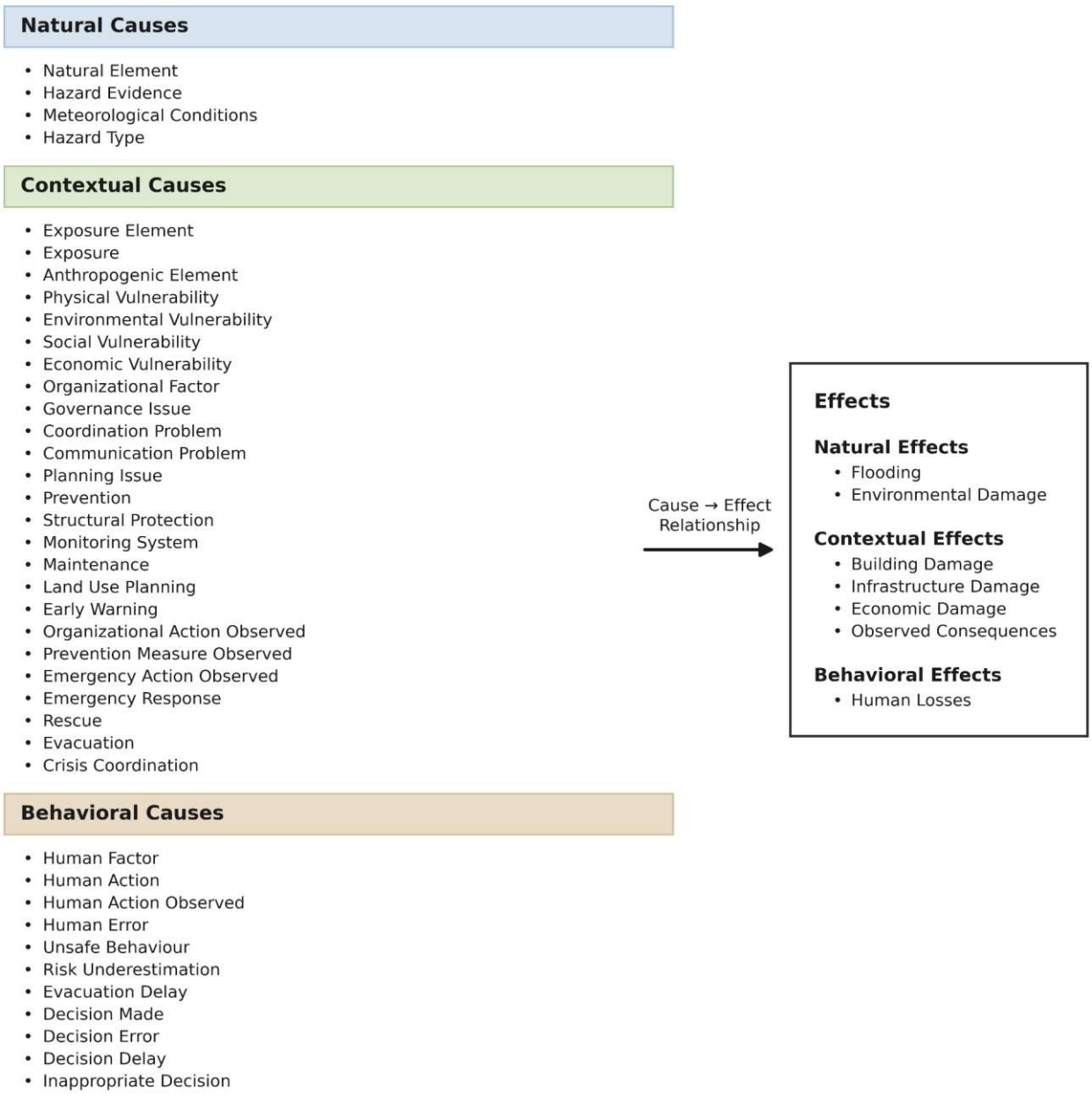


Figure 5. CLIMAgenAI Cause-effect framework for the catastrophic event assessment.

4. AI-supported knowledge translation: from causal analysis to awareness and stakeholder engagement

The structured outputs produced by the CLIMAgenAI framework — cause–effect matrix, reconstructed causal pathways and comparative analytical datasets — are not conceived solely as scientific deliverables. Their design is explicitly oriented towards the testing of an operational AI-driven solution designed for translating complex causal knowledge into accessible, actionable information for different audiences.

This section discusses the broader value of combining multi-source causal analysis with generative AI and outlines two main directions in which CLIMAgenAI outputs can be deployed: enhancing public awareness and climate literacy and supporting stakeholder engagement and participatory risk governance.

4.1 The role of AI in knowledge translation, public awareness and climate literacy

A critical challenge in climate risk communication is the gap between the complexity of analytical outputs and the capacity of varying audiences — from technical agency managers to the general public, citizens, local administrators, journalists and community representatives. Understanding, forecasting and managing causes and effects of natural disasters is still an unsolved problem. The gathering and interpretation of climate information and the capacity to properly act and take decision based on historical data and real time climate information is still a debated critical task. Large language models (LLMs) and generative AI tools offer a promising path to bridging this gap, as they can process structured data and generate narratives tailored to specific audiences, contexts and communication objectives (Bordes et al. 2024; Radford et al. 2021).

Within the CLIMAgenAI ecosystem, AI intervenes at the interface between the analytical layer — where causal knowledge is structured and formalized — and the communication layer, where this knowledge is translated into narratives, summaries and interactive representations. The cause–effect matrices and causal pathways produced by CLIMAgenAI serve as the factual and structural grounding for AI-generated outputs, ensuring that narratives remain anchored to documented evidence rather than abstract generalization. This design reflects a broader principle in responsible AI development: that generative models perform more reliably and accountably when their outputs are constrained by structured, verifiable knowledge bases (Bordes et al. 2024; Radford et al. 2021; Karpathy and Fei-Fei 2014).

The first direction of deployment concerns the use of AI tools to make climate risk knowledge accessible to the public. LLM-based systems can translate the technical outputs of CLIMAgenAI — including causal pathways, institutional failure patterns and event reconstructions — into plain-language narratives and news-style content, adapting complexity and tone to the intended audience. By grounding AI generation in structured causal datasets derived from judicial, archival and multimedia sources, the proposed approach and methodology ensure that public-facing content remains consistent with documented event dynamics, including specific omissions and institutional responsibilities identified through the analytical process.

Within this architecture, Figure 6 visualizes the multi-source information flow: CLIMAgenAI processes judicial, archival and multimedia sources, maps their content onto natural, contextual and behavioral cause and effect dimensions, and consolidates them into a standardized cause–effect matrix. In this way, the analytical layer provides a structured and source-aware foundation on which AI tools can operate, ensuring that knowledge translation remains grounded in documented causal pathways.

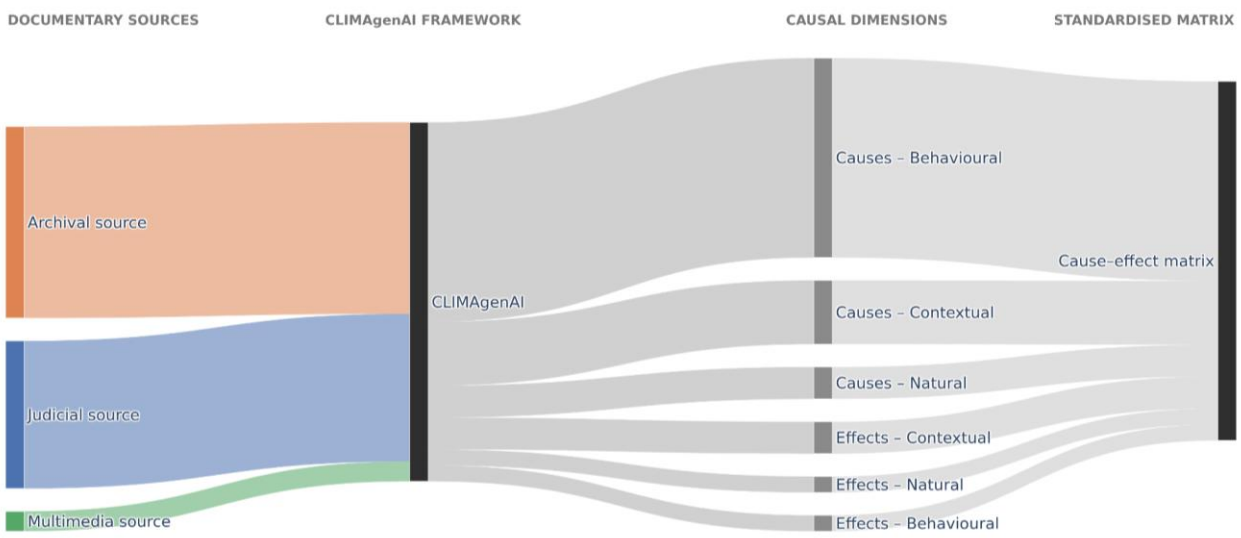


Figure 6. CLIMAgenAI multi-source framework: from documentary sources to cause - effect matrix.

The value of this application is twofold. First, it democratizes access to forensic climate risk knowledge, enabling non-specialist audiences to understand how disasters unfold, what governance failures contributed to their severity and what institutional responsibilities were documented. Second, it supports a culture of climate risk awareness grounded in evidence rather than abstract warnings, contributing to the broader goals of climate literacy and community resilience. AI tools in this context do not replace expert analysis but act as translators between the analytical layer and the public sphere, making complex causal structures legible without reducing their essential content.

4.2 AI for stakeholder engagement and knowledge co-production

A second direction concerns the use of AI-assisted interfaces to foster active engagement of stakeholders — including practitioners, local authorities, civil society organizations and researchers — in the interpretation, validation and use of climate risk knowledge. Rather than presenting analytical outputs as finished products, AI tools can support interactive exploration of reconstructed causal pathways, contextual explanation of causal links and identification of governance gaps and institutional vulnerabilities across cases and territories.

This model of AI-mediated engagement reflects a participatory approach to disaster risk governance, in which knowledge is not simply transferred from experts to users but co-constructed through dialogue between analytical outputs, local experience and institutional perspectives. AI interfaces can facilitate the comparison of causal configurations across events, support annotation and local knowledge contribution, and help stakeholders co-produce recommendations for risk governance and policy deliberation. By linking CLIMAgenAI's multi-source causal framework to interactive AI-supported environments, forensic risk analysis becomes a resource not only for scientific research but also for governance innovation and community-level risk reduction planning.

The use of AI tools for knowledge translation and stakeholder engagement also raises important questions about responsible design and deployment. Ensuring transparency in how analytical outputs are processed and narrated, avoiding oversimplifications that obscure causal complexity, and safeguarding sensitive information — particularly when judicial sources are involved — are critical requirements that must be addressed through careful governance of AI systems. Furthermore, the quality of AI-generated outputs depends directly on the quality and completeness of the underlying causal knowledge: errors or omissions in the CLIMAgenAI analytical process will propagate into AI-

generated narratives and interactive interfaces, underscoring the importance of rigorous methodological standards at every stage of the framework.

4.3 Methodological insights from the CLIMAgenAI framework application to the Sarno case study

To illustrate how CLIMAgenAI integrates heterogeneous sources into a single causal structure, the framework was applied to the 1998 Sarno debris-flow disaster. Figure 7 (Sarno case) shows how judicial, archival and multimedia sources contribute complementary information on the same event, and, in the lower panel, how these inputs are mapped onto the cause–effect matrix for natural, contextual and behavioral causes and their links to different impact dimensions (environmental, building, infrastructure, economic damage and human losses). From a methodological perspective, this case study highlights three key features of the framework rather than providing strong statistical results.

First, the matrix demonstrates the **multi-source nature** of each causal link: markers associated with judicial, archival and multimedia sources show not only which cause is documented, but also by which type of source, and where sources conflict (for instance in the reported number of fatalities) the matrix preserves multiple readings while explicitly recording agreement and disagreement.

Second, the Sarno application illustrates the **dimensional mapping** of causes: intense and prolonged rainfall, unstable pyroclastic covers and repeated debris flows are consistently classified as natural causes, while deforestation, settlement patterns at the mouths of the "Valloni", obstructed channels and the absence of telemetered rain gauges are treated as contextual causes, and emergency management failures — such as the absence of the local civil protection committee, televised reassurances and delayed evacuation — are coded as behavioral causes.

Third, the case shows how these causes are systematically linked to impact categories, allowing the reconstruction of distinct pathways leading to environmental damage, infrastructure damage and human losses.

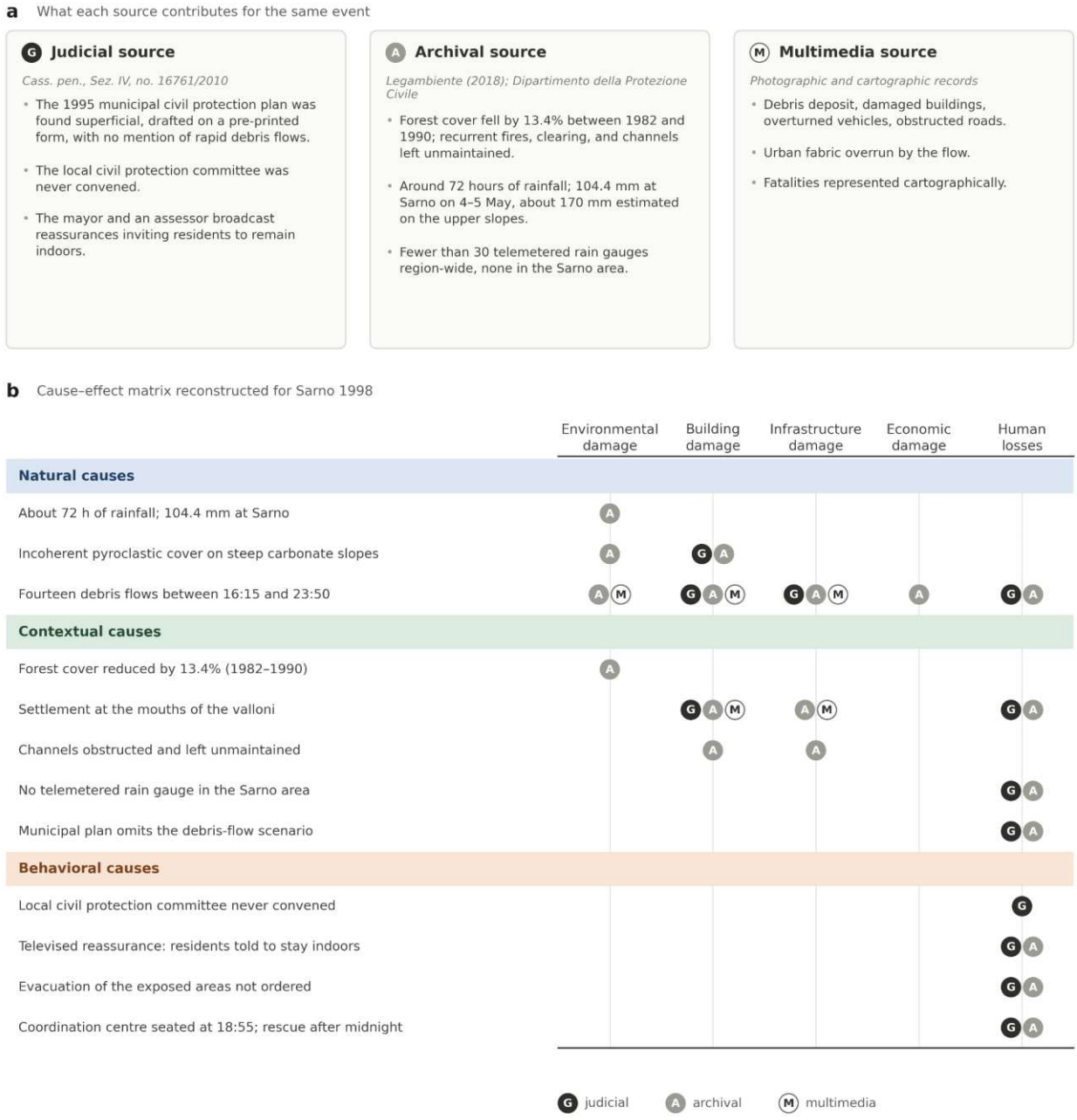


Figure 7. Cause-effect framework for the 1998 Sarno debris flow

Because the analysis focuses on a single event, the quantitative strength of the findings remains limited. Nevertheless, the Sarno case provides a **proof-of-concept** for the methodological robustness of CLIMAgenAI: it shows that judicial, archival and multimedia materials can be integrated into a unified, source-aware cause–effect matrix; that natural, contextual and behavioral dimensions can be consistently distinguished and that institutional vulnerabilities — such as failures in emergency planning and communication — can be traced along causal pathways from upstream conditions to downstream impacts. These properties are essential preconditions for the subsequent use of CLIMAgenAI outputs in AI-supported knowledge translation and stakeholder engagement, as they guarantee that the structured data feeding AI tools encapsulate not only event dynamics but also the provenance and reliability of the underlying documentary evidence.

5. Conclusions, limitations and future developments

This study has introduced CLIMAgenAI as an innovative methodological framework for analyzing climate risk through the systematic integration of heterogeneous documentary sources and the reconstruction of causal relations underlying disaster events. By adapting the cause–effect matrix to judicial rulings, archival records and multimedia materials — and by grounding this adaptation in the complementary principles of FTA, ETA and HOFE — the framework offers a replicable, transdisciplinary procedure for transforming complex narrative and visual documents into structured analytical datasets and comparable causal pathways.

The central contribution of CLIMAgenAI lies in its capacity to treat exposure and vulnerability not as predefined variables, but as empirically reconstructed outcomes of governance arrangements, institutional decisions and human behaviors. Within the CLIMAgenAI framework, exposure and vulnerability are used to enable the systematic quantification of the human component by analyzing and interpreting human perception, decisions, actions and behaviours, together with their causal roles and consequences throughout the investigated climate disaster. This information supports disaster risk assessment, mitigation and governance. This shift from a variable-based to a process-based approach to risk analysis makes it possible to capture biophysical, contextual and behavioral dimensions of climate risk that remain invisible or fragmented in conventional assessments — including the role of administrative omissions, coordination failures and decision-making dynamics in amplifying disaster outcomes. The application to the Sarno debris-flow disaster demonstrated how CLIMAgenAI effectively integrated multi-source documentary evidence into a unified, source-aware cause–effect matrix and used to trace institutional vulnerabilities along causal pathways from upstream conditions to downstream impacts.

A second contribution concerns the framework's potential for integration with generative AI tools. By producing structured causal knowledge — matrices, pathways and coded datasets — CLIMAgenAI creates the informational foundation that AI systems require to generate reliable, evidence-grounded narratives and interactive interfaces. This connection between forensic risk analysis and AI-supported knowledge translation opens new possibilities for climate risk communication, public awareness and participatory governance, placing structured causal knowledge at the service of broader societal processes rather than confining it to specialist scientific use.

Like any methodological proof-of-concept, this study has several limitations. First, the framework is demonstrated through a single case study, the 1998 Sarno debris-flow disaster, selected because it represents one of the most comprehensively documented climate-related disasters in Italy. The event generated an exceptional body of judicial rulings, institutional reports, archival records and multimedia documentation, and had a profound societal and political impact, ultimately contributing to the reform of the national legislative and institutional framework for hydrogeological risk management. While this richness makes Sarno an ideal benchmark for testing the proposed methodology, additional applications to different hazards, geographical settings and documentary contexts are required to fully assess its generalizability. Second, the AI component presented in this work is intentionally limited to the use of standard generative AI models, albeit operating within a rigorously defined analytical workflow. The novelty of the study therefore lies in the structured causal framework rather than in the development of new AI algorithms, and future research should investigate more advanced AI architectures, retrieval strategies and automated causal extraction methods. Finally, although the framework introduces standardized coding rules and source reliability criteria, parts of the analytical process still require expert judgement, particularly in the interpretation of complex documentary evidence and causal attribution. Further methodological refinement, including automated coding support and formal inter-coder validation, will be essential to strengthen reproducibility, reduce subjectivity and facilitate large-scale operational applications.

As a result, several directions for future development remain open. First, the framework should be extended and validated across a broader range of hazard types, geographic contexts and legal systems, moving beyond the Italian case studies that have informed its current design. Second, the coding

procedures — particularly those for causal categorization and reliability verification — should be further formalized and tested for inter-coder consistency, to strengthen the replicability of the analytical process. Third, the interface between CLIMAgenAI outputs and AI generation systems requires dedicated research, addressing questions of prompt design, output quality evaluation and the governance of AI tools operating on sensitive judicial and archival materials. Together, these developments would allow CLIMAgenAI to mature from a methodological proposal into a validated, scalable tool for forensic climate risk analysis and AI-supported disaster governance.

References

Akçay Zileli, Yaprak. 2023. "Development of a Risk Management Model by the Fuzzy DEMATEL Method in the Evaluation of Authorized Certification Bodies." In *Risk Management, Sustainability and Leadership*, edited by Larisa Ivascu, Ben-Oni Ardelean, and Muddassar Sarfraz. IntechOpen. https://doi.org/10.5772/intechopen.110018.

Attoh, Emmanuel M. N. A. N., and Giriraj Amarnath. 2025. "A Framework for Addressing the Interconnectedness of Early Warning to Action and Finance to Strengthen Multiscale Institutional Responses to Climate Shocks and Disasters." *Climate Risk Management* 47 (January): 100689. https://doi.org/10.1016/j.crm.2025.100689.

Aven, Terje. 2016. "Risk Assessment and Risk Management: Review of Recent Advances on Their Foundation." *European Journal of Operational Research* 253 (1): 1–13. https://doi.org/10.1016/j.ejor.2015.12.023.

Aven, Terje. 2025. "On the Relationship between Disaster Risk Science and Risk Science." *Risk Analysis* 45 (9): 2494–503. https://doi.org/10.1111/risa.70045.

Bacon, Benjamin Wisner, ed. 2010. *At Risk: Natural Hazards, People's Vulnerability and Disasters*. 2. ed., Reprinted. Routledge.

Baraldi, Piero, and Enrico Zio. 2008. "A Combined Monte Carlo and Possibilistic Approach to Uncertainty Propagation in Event Tree Analysis." *Risk Analysis* 28 (5): 1309–26. https://doi.org/10.1111/j.1539-6924.2008.01085.x.

Basu, Swapan. 2017. *Plant Hazard Analysis and Safety Instrumentation Systems*. Elsevier. https://doi.org/10.1016/C2015-0-00253-2.

Birkmann, Jörn, ed. 2013. *Measuring Vulnerability to Natural Hazards: Towards Disaster Resilient Societies*. 2. ed. United Nations Univ. Press.

Boin, Arjen, Paul 'T Hart, Eric Stern, and Bengt Sundelius. 2005. *The Politics of Crisis Management: Public Leadership Under Pressure*. 1st ed. Cambridge University Press. https://doi.org/10.1017/CBO9780511490880.

Bordes, Florian, Richard Yuanzhe Pang, Anurag Ajay, et al. 2024. "An Introduction to Vision-Language Modeling." Version 1. Preprint, arXiv. https://doi.org/10.48550/ARXIV.2405.17247.

Brignone, Marta, Fabrizio Santamato, Marco Ravina, Valentina Busini, and Deborah Panepinto. 2025. "NaTech Database and Methodologies for Its Risk Assessment: A Review." *Natural Hazards* 121 (17): 19565–90. https://doi.org/10.1007/s11069-025-07562-z.

Čepin, Marko. 2011. “Event Tree Analysis.” In *Assessment of Power System Reliability*, by Marko Čepin. Springer London. https://doi.org/10.1007/978-0-85729-688-7_6.

Donati, Edda and Fernando Nardi. «Floods on Trial: Transdisciplinary Human Accountability for Improving Disaster Governance». International Journal of Disaster Risk Reduction 143 (september 2026): 106290. https://doi.org/10.1016/j.ijdrr.2026.106290.

Duijm, Nijs Jan. 2015. “Recommendations on the Use and Design of Risk Matrices.” *Safety Science* 76 (July): 21–31. https://doi.org/10.1016/j.ssci.2015.02.014.

Ehiagwina, Frederick Ojiemhende. 2022. *Fault Tree Analysis and Its Modifications as Tools for Reliability and Risk Analysis of Engineering Systems – An Overview*.

Ekström, Marie, Natasha Kuruppu, Robert L. Wilby, et al. 2013. “Examination of Climate Risk Using a Modified Uncertainty Matrix Framework—Applications in the Water Sector.” *Global Environmental Change* 23 (1): 115–29. https://doi.org/10.1016/j.gloenvcha.2012.11.003.

Fajardo-Gonzalez, Johanna, C. A. Knox Lovell, Julie Lovell, and Heidi Edmonds. 2025. “Measuring Climate Risks: A New Multidimensional Index for Global Vulnerability and Resilience.” *Environmental Development* 56 (September): 101227. https://doi.org/10.1016/j.envdev.2025.101227.

Ferdous, Refaul, Faisal Khan, Rehan Sadiq, Paul Amyotte, and Brian Veitch. 2009. “Handling Data Uncertainties in Event Tree Analysis.” *Process Safety and Environmental Protection* 87 (5): 283–92. https://doi.org/10.1016/j.psep.2009.07.003.

Ferdous, Refaul, Faisal Khan, Rehan Sadiq, Paul Amyotte, and Brian Veitch. 2013. “Analyzing System Safety and Risks under Uncertainty Using a Bow-Tie Diagram: An Innovative Approach.” *Process Safety and Environmental Protection* 91 (1): 1–18. https://doi.org/10.1016/j.psep.2011.08.010.

Gallina, Valentina, Silvia Torresan, Andrea Critto, Anna Sperotto, Thomas Glade, and Antonio Marcomini. 2016. “A Review of Multi-Risk Methodologies for Natural Hazards: Consequences and Challenges for a Climate Change Impact Assessment.” *Journal of Environmental Management* 168 (March): 123–32. https://doi.org/10.1016/j.jenvman.2015.11.011.

Hochrainer-Stigler, Stefan, Teresa Maria Deubelli-Hwang, Janne Parviainen, Lydia Cumiskey, Pia-Johanna Schweizer, and Ulf Dieckmann. 2024. “Managing Systemic Risk through Transformative Change: Combining Systemic Risk Analysis with Knowledge Co-Production.” *One Earth* 7 (5): 771–81. https://doi.org/10.1016/j.oneear.2024.04.014.

Huang, He, Honglei Wang, Yu Jie Hu, Chengjiang Li, and Xiaolin Wang. 2022. “The Development Trends of Existing Building Energy Conservation and Emission Reduction—A Comprehensive Review.” *Energy Reports* 8 (November): 13170–88. https://doi.org/10.1016/j.egyr.2022.10.023.

ICCD – Istituto Centrale per il Catalogo e la Documentazione. 2005. Catalogazione dei beni culturali: scheda OA – Oggetto d’arte. Esempio di compilazione (Cataloguing of Cultural Heritage: OA Sheet – Work of Art. Example of Compilation). Regione Emilia-Romagna, Istituto per i beni artistici, culturali e naturali.

Karpathy, Andrej, and Li Fei-Fei. 2014. “Deep Visual-Semantic Alignments for Generating Image Descriptions.” Version 2. Preprint, arXiv. https://doi.org/10.48550/ARXIV.1412.2306.

Khan, Faisal I., and Tahir Husain. 2001. “Risk Assessment and Safety Evaluation Using Probabilistic Fault Tree Analysis.” *Human and Ecological Risk Assessment: An International Journal* 7 (7): 1909–27. https://doi.org/10.1080/20018091095483.

Moseman, James A. 2024. “Retrospective on the Risk Matrix, Part 1.” *Process Safety Progress* 43 (2): 270–77. https://doi.org/10.1002/prs.12540.

Moser, Susanne C., and Julia A. Ekstrom. 2010. “A Framework to Diagnose Barriers to Climate Change Adaptation.” *Proceedings of the National Academy of Sciences* 107 (51): 22026–31. https://doi.org/10.1073/pnas.1007887107.

O’Brien, Karen, Siri Eriksen, Lynn P. Nygaard, and Ane Schjolden. 2007. “Why Different Interpretations of Vulnerability Matter in Climate Change Discourses.” *Climate Policy* 7 (1): 73–88. https://doi.org/10.1080/14693062.2007.9685639.

Osborne, Stephen P., and Sarah-Sophie Fleming. 2015. “CONCEPTUALIZING RISK AND SOCIAL INNOVATION: AN INTEGRATED FRAMEWORK FOR RISK GOVERNANCE.” *Society and Economy* 37 (2): 165–82. JSTOR.

Pahl-Wostl, Claudia. 2009. “A Conceptual Framework for Analysing Adaptive Capacity and Multi-Level Learning Processes in Resource Governance Regimes.” *Global Environmental Change* 19 (3): 354–65. https://doi.org/10.1016/j.gloenvcha.2009.06.001.

Pasman, Hans J., and William J. Rogers. 2020. “Chapter Three - Logic Based Methods for Dynamic Risk Assessment.” In *Methods in Chemical Process Safety*, edited by Faisal I. Khan and Paul R. Amyotte, vol. 4. Elsevier. https://doi.org/10.1016/bs.mcps.2020.02.001.

Radford, Alec, Jong Wook Kim, Chris Hallacy, et al. 2021. “Learning Transferable Visual Models From Natural Language Supervision.” Version 1. Preprint, arXiv. https://doi.org/10.48550/ARXIV.2103.00020.

Rasmussen, Jens. 1997. “Risk Management in a Dynamic Society: A Modelling Problem.” *Safety Science* 27 (2): 183–213. https://doi.org/10.1016/S0925-7535(97)00052-0.

Rosqvist, Tony, Riitta Molarius, Hanna Virta, and Adriaan Perrels. 2013. “Event Tree Analysis for Flood Protection—An Exploratory Study in Finland.” *Reliability Engineering & System Safety* 112 (April): 1–7. https://doi.org/10.1016/j.ress.2012.11.013.

Skogdalen, Jon Espen, and Jan Erik Vinnem. 2011. “Quantitative Risk Analysis Offshore—Human and Organizational Factors.” *Reliability Engineering & System Safety* 96 (4): 468–79. https://doi.org/10.1016/j.ress.2010.12.013.

Tierney, Kathleen. 2012. “Disaster Governance: Social, Political, and Economic Dimensions.” *Annual Review of Environment and Resources* 37 (1): 341–63. https://doi.org/10.1146/annurev-environ-020911-095618.

Tierney, Kathleen J. 2014a. *The Social Roots of Risk: Producing Disasters, Promoting Resilience*. High Reliability and Crisis Management. Stanford business books.

Tierney, Kathleen J. 2014b. *The Social Roots of Risk: Producing Disasters, Promoting Resilience*. High Reliability and Crisis Management Ser. Stanford University Press.

Trist, E. L., and K. W. Bamforth. 1951. "Some Social and Psychological Consequences of the Longwall Method of Coal-Getting: An Examination of the Psychological Situation and Defences of a Work Group in Relation to the Social Structure and Technological Content of the Work System." *Human Relations* 4 (1): 3–38. https://doi.org/10.1177/001872675100400101.

Wessiani, N. A., and F. Yoshio. 2018. "Failure Mode Effect Analysis and Fault Tree Analysis as a Combined Methodology in Risk Management." *IOP Conference Series: Materials Science and Engineering* 337 (April): 012033. https://doi.org/10.1088/1757-899X/337/1/012033.

Yazdi, Mohammad, Javad Mohammadpour, He Li, et al. 2023. "Fault Tree Analysis Improvements: A Bibliometric Analysis and Literature Review." *Quality and Reliability Engineering International* 39 (5): 1639–59. https://doi.org/10.1002/qre.3271.